International Financial Transmission: Emerging and Mature Markets*

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Abstract

With an increasingly integrated global financial system, we frequently observe that shocks to individual asset markets affect financial markets worldwide. The aim of this paper is to quantify the comovements between bond markets in the US and emerging market economies. Following Rigobon (2003), we exploit the changing volatility of the data to fully identify a structural VAR, without imposing ad-hoc restrictions. Our results yield some new insights into how shocks are transmitted across international financial markets.

JEL classification: F30, G15, C32

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1 Introduction

Financial markets worldwide are becoming increasingly integrated. One consequence of this is that we observe a large degree of comovement across financial markets, as shocks to individual markets or countries are transmitted internationally. Such spill-over effects were most notable during several financial crises episodes in emerging market economies (EMEs) over the past decade. From a central banking perspective, understanding the mechanisms through which shocks are transmitted across financial markets is important for gauging the extent to which financial crises and volatility in emerging market economies can affect the financial systems in developed countries, and *vice versa*.

The aim of this paper is to quantify the linkages between bond markets in the U.S. and EMEs. We are particularly interested in two questions. First, what is

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the relationship between US interest rates and emerging market bond spreads? On the one hand, an intuitive argument suggests that rising US interest rates should increase the financing costs of EMEs, thus raising their default risk and increasing the spreads that EME borrowers have to pay over risk-free rates. Furthermore, decreases in riskless rates are often thought to be associated with a "search for yield", as investors shift into more risky assets such EME debt and drive their spreads down. On the other hand, episodes of emerging market turmoil often seem to be associated with a "flight to quality" and thus a negative effect of EMBIG spreads and risk-less rates, as investors shift out of risky assets and into "safe-haven" assets such as US government debt. However, previous studies have failed to find clear evidence of a positive effect of US interest rates on EME bond spreads[1], and only few studies have sought to quantify the reverse influence of EMEs on financial markets in mature economies[2].

A second question concerns the relationship between spreads on risky debt in emerging and mature markets. It is well known that EMBIG and US high yield spreads tend to move together. But are US high yield spreads influencing EMBIG spreads, or does the influence run the other way round? This relationship is particularly important because it represents one possible channel through which EME crises might negatively affect mature markets.

Studies of financial market comovement are often complicated by endogeneity bias. When two variables, such as US government bond yields and EMBIG spreads, are both endogenous, estimation results in structural models will be biased. To circumvent this bias, researchers have typically resorted to restrictions, effectively imposing that influences run only one-way. We do not want to impose such restrictions because it is precisely the direction of influence that we are trying to uncover. Using a relatively new methodology, we are able to estimate a structural VAR model without imposing the ad hoc restrictions that are commonly used for identification in the VAR literature. Following Rigobon (2003), we exploit the changing volatility of the data to identify our model. The crucial assumption underlying this methodology is that the coefficients describing the comovement of our endogenous variables are constant over the whole sample period: our results should therefore be thought of as capturing average, long-run effects.

Our results shed light on how structural shocks to individual variables are transmitted through the system. We can distinguish between *direct* and *overall* spillover effects. An initial structural shock that increases EMBIG spreads has direct effects on the other variables: for example, it reduces US long-term government bond yields and increases US high yield spreads. However, following this first round of spillover effects, lower US government bond yields may feed back on the US high yield market, which could in turn affect EMBIG spreads and so forth. The overall effects of the initial structural shocks tend to have the same sign as the direct effects, although the magnitude typically differs.

We find strong evidence for "flight to quality": EME structural shocks tend

[1] See e.g. Eichengreen and Mody (1998).

[2] See for example Sáez, Fratzscher and Thiemann (2007), who study the effects of EME shocks on global equity markets.

to lower US government bond yields, especially long-term ones. Conversely, the evidence for the financing cost argument appears to be more mixed. We find that the *overall* effect of shocks to US long-term rates on EMBIG spreads is negative and thus has the "wrong" sign. This is in line with the previous empirical literature. However, we do find a positive *direct* effect of US long-term government bond yields on EMBIG spreads, although the coefficient is close to zero and not statistically significant. This suggests that although the direct effect of a rise in US interest rates may be to raise the financing costs of EMEs, this effect is very weak and has been difficult to detect in previous studies because it is dominated by second-round effects that run through third variables.

We also find strong spillover effects both from EMBIG to US high yield spreads and *vice versa*. One explanation for this comovement is that an increase in risk aversion causes investors to shift out of risky assets, including both US corporate and EME bonds, in response to disruptive shocks. This suggests that the high yield market is an important channel through which financial crises can spread. For example, mature markets may be adversely affected by crises in EMEs when US high yield spreads rise (as in the Russian/LTCM crisis 1998) and firms find it more expensive to access the debt markets.

While we allow for heteroskedastic structural shocks (indeed, this heteroskedasticity is crucial to identify the model), we assume that the coefficients are stable. Is this assumption justified? Intuitively, the effect of an EME shock on US high yield spreads (to take an example) is given by the estimated coefficient times the size of the shock. Thus, as the size of the shock to EME spreads varies (between tranquil and crisis periods in EMEs), so will the spillover effect between EMEs and mature markets. We check for parameter stability by estimating the model separately for the first and second half of the sample. Although parameters do change quantitatively, their sign is the same across both periods. This is remarkable, especially given the fact that the volatility of EMEs has declined substantially over the later part of the sample. We view this result as evidence that our assumption of stable coefficients is justified. Also, for the reduced form model the null hypothesis of parameter stability is not rejected in a standard multivariate Chow test.

A crucial step in our estimation procedure is the identification of volatility regimes. The idea in choosing regimes is to identify periods in which the volatility of the underlying unobserved structural shocks differs. We employ two different methods of regime choice to check whether our results are robust to the exact regimes chosen. We also discuss how our choice of volatility regimes corresponds to actual events, such as for example financial crises in EMEs.

The theoretical literature on financial markets and contagion has identified several channels through which shocks may be transmitted across financial markets[3], and there is a large number of empirical studies on the comovement of

[3]Examples include the correlated information channel (King and Wadhwani, 1990), links between financial institutions (Allen and Gale, 2000), portfolio rebalancing (Kodres and

international financial markets. The empirical literature can be roughly classified into two broad strands: studies on the (long-run) comovement of financial markets, and studies analysing "contagion", typically defined as an increase in the correlation between markets in times of crises.[4] Research in the first strand has generally focused exclusively on the comovement of markets for just one asset class (typically stock markets). Furthermore, most studies either do not identify the contemporaneous feedback effects between the endogenous variables, or use standard, but *ad-hoc* restrictions for identification. An exception to both of these limitations is the paper by Ehrmann, Fratzscher and Rigobon (2005), who analyse the interlinkages between US and European financial markets (including bonds, stocks, and exchange rates), employing the method developed in Rigobon (2003) to identify a structural VAR.

Empirical research in the second strand has attempted to establish whether or not contagion occurred, based on two different methodologies: tests for increases in correlations in crisis times[5], and also whether the probability of a crisis in some market A, given that there is a crisis in market B, is higher than the unconditional probability. However, the literature on contagion faces the same identification challenges mentioned above, which have to be circumvented by making restrictive assumptions. For example, Favero and Giavazzi (2002) test for nonlinearities in the transmission of shocks in European money markets; to identify their model, they have to assume that several reduced-form coefficients are equal to zero.

A further problem in testing whether financial transmission channels change in times of crisis is the specification of the crisis window. If these windows are specified ex post, tests for contagion are likely to be severly biased (see Pesaran and Pick, 2006). For example, Carporale, Cipollini and Demetriades (2005) study the relationship between interest rates and exchange rates during the Asian crisis (1997-8) using a methodology similar to ours. They include dummies to allow for the possiblity that coefficients change during the crisis, but set these dummies exogenously rather than within the model.

To sum up, the empirical literature on the comovement of international financial markets has the following limitations: (i) identification challenges have usually forced researchers to impose *ad-hoc* restrictions on the contemporaneous feedback effects among the endogenous variables; (ii) research has typically focused on comovement of markets for one specific asset, rather than linkages across asset classes as well as across countries. Addressing these limitations, our contribution is to analyse the relationships between bond markets in the US and EMEs, and to identify how shocks across markets without imposing unrealistic restrictions. Our paper assumes that the transmission channels are constant across the whole sample period as we aim to capture average, long-run

Pritsker, 2002), herd behavior (Calvo and Mendoza, 2000; Chari and Kehoe, 2003), wealth effects (Kyle and Xiong, 2001), and the role of information markets (Veldkamp, 2006).

[4] See Gagnon and Karolyi (2006) for an extensive review of the empirical literature on comovement of international financial markets, and Dornbusch, Claessens and Park (2000) and Dungey et.al. (2003) for surveys on the empirical literature on contagion.

[5] For example, Forbes and Rigobon (2002).

linkages between markets rather than possible changes in contagion episodes. To our knowledge, this study is the first to analyse comovement between financial markets in EMEs and developed countries using the Rigobon (2003) methodology.

Our paper is structured as follows. The next section reviews some stylised facts about the correlations of our endogenous variables for tranquil and crisis periods. These findings are important for interpreting our final results concerning the comovements of financial markets, and they are also useful for deciding on starting values for estimation of our model. The third section gives a brief introduction to the empirical methodology that we use, "Identification through heteroskedasticity", and outlines our empirical model and the choice of volatility regimes. The fourth section then presents the results. Section six presents some robustness checks. In particular, we estimate our model separately for the first and second part of the sample to check whether parameters can indeed be considered to be stable over time, as assumed. Furthermore, we employ an alternative method of regime choice to test the sensitivity of our results to the method of regime choice employed. Finally, section six concludes and discusses avenues for future research.

2 Comovement of international financial markets: some stylised facts

Before we begin with the formal empirical analysis it is useful to look at some simple statistics of the raw data to get an idea of the relevant stylised facts. Our dataset includes daily data on US short- (3 month) and long-term (10 year) government bond yields, US high yield spreads, and EMBIG spreads, from January 1997 to December 2006. In our empirical analysis below we will work with data in first differences in order to ensure stationarity.

Table 1 presents correlations of the differenced raw data, computed over the whole sample period. Note first that US short- and long-term government bond yields are positively correlated, but negatively correlated with US high yield spreads. This second finding seems to contradict the conventional wisdom that higher risk-free interest rates should increase the financing costs of risky borrowers and hence their default risk, which should be reflected in spreads. Furthermore, since spreads are computed as the difference between the yields of risky and risk-less assets with corresponding maturity, spreads should be

Table 1: Correlations, 1997-2006

	US 3m	**US 10y**	**US HY**	**EMBIG**
US 3m	1.00			
US 10y	0.29	1.00		
US HY	-0.12	-0.32	1.00	
EMBIG	-0.06	-0.12	0.17	1.00

Data in first differences.

increasing in risk-less rates for simple "mathematical" reasons.[6] One possible explanation for this puzzle could be that US high yields spreads tend to be low when the US economy is booming and profits in the corporate sector are high. During such economic upturns, inflationary pressures may build up that induce monetary policymakers to raise interest rates, which then translates into higher long term rates, leading to a negative correlation between spreads on risky debt and risk-less rates.

The correlation between EMBIG and US high yield spreads is positive, suggesting a high degree of comovement across markets. Finally, the correlations between EMBIG spreads and US government bond yields are negative - again, this is surprising. We would expect correlations between EMBIG spreads and risk-less US government bond yields to be positively correlated: higher risk-less rates should increase financing costs and hence the default risk of risky borrowers; furthermore, following a decrease in risk-less rates, investors tend to "search for yield" and shift into more risky assets in order to earn higher returns, thus driving the prices of these assets up and their yield spreads over risk-less debt down.[7]

It is interesting to also look at how correlations change during periods of financial market turmoil. As an example, Table 2 summarises the correlations for the period of the Russian/LTCM crisis 1998. Note that the magnitude of all correlations increases, while the sign of the correlation coefficients stays the same. The strong correlation between EMBIG spreads and US high yield in that period is an indication of the contagion that occurred following the Russian default, possibly through an increase in investors' risk aversion. The

[6] To see this, consider the following simple example taken from Kamin and von Kleist (1999). Let i denote the yield of a risky asset which is repaid with probability p, and r denote the yield of a corresponding risk-less asset. Then we have

$$1 + r = p \cdot (1 + i) + (1 - p) \cdot 0$$

From this, the spread is computed as

$$i - r = \frac{(1 + r)(1 - p)}{p}$$

which is increasing in r.

[7] Note however that correlations of US government bond yields and EMBIG spreads are positive when the variables are analysed in levels.

Table 2: Correlations during the Russian/LTCM crisis

	US 3m	**US 10y**	**US HY**	**EMBIG**
US 3m	1.00			
US 10y	0.49	1.00		
US HY	-0.26	-0.74	1.00	
EMBIG	-0.21	-0.45	0.55	1.00

Data in first differences.

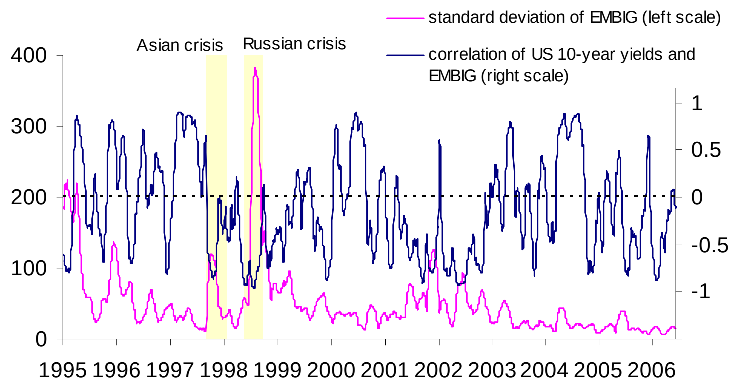
strong negative correlation between US government bond yields and EMBIG spreads may reflect the "flight to quality".

Figure 1 plots the correlation between US long-term government bond yields and EMBIG spreads versus EMBIG volatility (computed over rolling windows of 21 days) to illustrate how correlations change in times of financial market volatility. The Asian (1997-8) and Russian (1998) financial crises are marked by spikes in EMBIG volatility, and by a corresponding fall of the correlation between EMBIG and US long-term yields. Again, this could be interpreted as a "flight to quality", as well as resulting from the provision of ample liquidity by the Federal Reserve in the face of the LTCM crisis.

There are two ways to interpret these findings. First, the changing correlations in time of financial market turmoil could imply that the relationship between our variables is non-linear, so that spillover effects change in times of high volatility. This is the approach taken by the empirical literature on financial contagion. In contrast, for our econometric model we will assume that the underlying parameters that govern the feedback effects between variables stay the same, and it is only the size and volatility of the underlying structural shocks that change. Therefore different transmission channels will dominate in times of crises.

Correlations indicate how financial variables move together, but do not provide information about the source of that comovement. A high correlation between EMBIG spreads and US government bond yields could be caused by EMBIG spreads affecting US interest rates (e.g., flight to quality); by US interest rates affecting EMBIG spreads (e.g., financing costs); or causation could run through some third factor such as US high yield spreads (e.g., a financial crisis in some EME increases EMBIG spreads, and US high yield spreads increase as well because of higher risk aversion; to ease the burden on the economy, the Federal Reserve lowers interest rates). To analyse through which channels these feedback effects occur, we estimate a fully identified structural VAR below.

Figure 1: Correlation of US long-term government bond yields and EMBIG spreads



EMBI before 1998. Volatility and correlations computed over 61-day windows.

3 Empirical methodology

3.1 Some intuition: identification through heteroskedasticity

Figure 2 plots the volatility of EMBIG spreads, computed over fixed windows of 60 days. Notice that the time series is highly heteroskedastic: episodes of EME crises are clearly marked by higher volatility. Rather than presenting a problem for estimation, this heteroskedasticity can actually be used to identify the model. This method was developed in Rigobon (2003) and labelled "identification through heteroskedasticity".

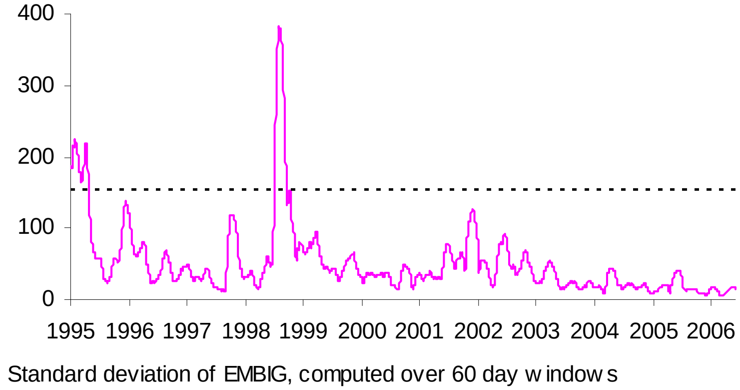
To illustrate this identification method, consider a model with only two variables - say, EMBIG spreads and US government bond yields. Both variables should be treated as endogenous: following our intuition from the previous section, a rise in US interest rates may increase EMBIG spreads, while a rise in EMBIG spreads could also reduce US interest rates (e.g., if flight to quality occurs). Thus the relationship between EMBIG spreads and US 10-year interest rates might be captured by the equations below:

$$EMBIG_t = \alpha \cdot US10_t + \epsilon_t \tag{1}$$

$$US10_t = \beta \cdot EMBIG_t + \eta_t \tag{2}$$

where ε_t and η_t are structural shocks. We expect $\alpha > 0$ and $\beta < 0$. This situation is captured in the left panel of figure 3. A dataset of observations on EMBIG and US interest rates might look like the scatterplot on the right panel of figure 3. Clearly, it is impossible to separately identify the two relationships

Figure 2: Volatility of EMBIG spreads



in (1) and (2). More formally, equations (1) and (2) can not be estimated directly because of endogeneity bias.

Now, suppose that we could distinguish periods in which the volatility of EMBIG spreads increases, while the volatility of US interest rates stays constant or increases only slightly. For example, in figure 2, we could pick periods in which volatility is above the upper 95% confidence bound, indicated by the dashed line. We could interpret the heterogeneity observed in the EMBIG and US interest rates as stemming from varying volatility in the structural shocks ε_t and η_t. Such a situation is plotted in the left panel of figure 4. Notice that the EMBIG volatility traces out relationship in equation (1). Similarly, the right panel of figure 4 shows how the relationship in equation (2) is traced out during periods of high US interest rate volatility. This is intuitive: in times of high US interest rate volatility, the effect of US interest rates on the financing costs of sovereign borrowers may dominate the data, and we are likely to find a positive correlation corresponding to equation (1). In times of EME crisis, the relationship between US interest rates and EMBIG spreads may be dominated by flight to quality, allowing us to identify equation (2). Thus, estimating our model separately for periods of different volatility can help to identify the model.

Note that the choice of regimes is very important to properly identify the model: identification works best if the change in relative volatilities is large across regimes, as shown in figure 4. The next section introduces our empirical model and explains identification through heteroskedasticity more formally.

3.2 The empirical model

We use a vector autoregressive model to account for the fact that no variable is truly exogenous. Following Rigobon (2005), our structural model is given

Figure 3: The identification problem

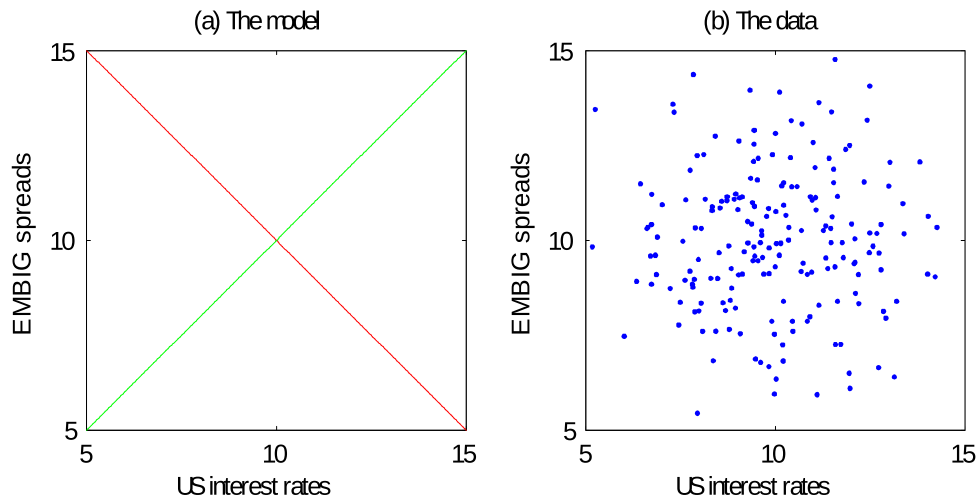
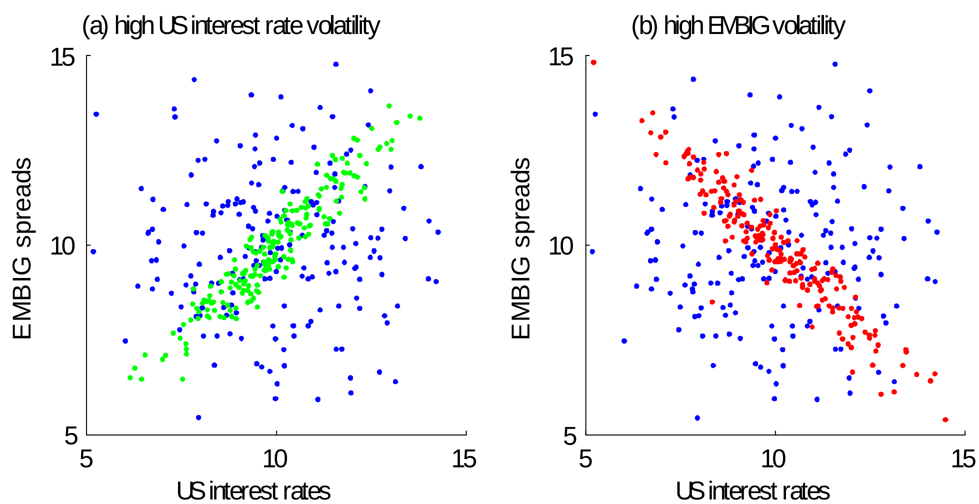


Figure 4: Identification through heteroskedasticity



by

$$Ay_t = \vartheta(t) + \Pi(L)y_{t-1} + \Gamma z_t + \mu_t \tag{3}$$

where y_t is the vector of endogenous variables, z_t is a vector of common shocks, and μ_t is a vector of structural shocks. A, $\Pi(L)$ and Γ are parameter matrices. Of particular interest to us is the matrix A, which determines the contemporaneous feedback effects among the endogenous variables. The matrix $\vartheta(t)$ includes constants and a time trend. We make the following standard assumptions:

$$E(\mu_t) = E(z_t) = 0$$

$$E(\mu_t \mu'_{t-i}) = E(z_t z_{t-j}) = E(\mu_t z_{t-k}) = 0$$

$\forall i, j, k \neq 0$. In order for our identification scheme to work, we need to assume restrict the covariances of some structural shocks to equal zero. Including a common shock then amounts to allowing the underlying shocks that drive the system to have some correlation.

To capture the changing volatility of our endogenous variables that we observe in the data, we allow the variances of both structural and common shocks to change across the sample. In particular, we assume that there are $s = 1, ..., S$ volatility periods or regimes, and that the shock variances are constant within each regime, but different across regimes. For each regime s, we have

$$\begin{aligned} E\left(\mu_t \mu'_t\right) &= \Omega_{\mu,s} \\ E\left(z_t^2\right) &= \Omega_{z,s} \end{aligned}$$

We cannot estimate equation (3) directly because of endogeneity bias. Therefore, we need to multiply work with the reduced form model, which is computed by multiplying both sides of (3) with A^{-1}. This yields

$$y_t = B_0 + B_1 y_{t-1} + u_t \tag{4}$$

where $B_0 = A^{-1}\vartheta$, $B_1 = A^{-1}\Pi(L)$ and $u_t = A^{-1}\Gamma z_t + A^{-1}\mu_t$. Since the same variables appear on the right hand side of every equation in (4), OLS can be used to estimate the reduced form parameters B_0 and B_1.[8] However, we want to go further and identify the structural parameters in the matrices A,Γ and ϑ. To do this, we can use "Identification through Heteroskedasticity", implemented through GMM estimation. Clearly, the residuals from the regression in (4) will reflect the underlying structural shocks μ_t. Therefore it is natural to use the residuals to determine volatility regimes for the structural shocks. How this can be done is described in the next section.

To obtain moment conditions for GMM estimation, rearrange equation (4) to yield

$$y_t - B_0 + B_1 y_{t-1} = A^{-1}\Gamma z_t + A^{-1}\mu_t$$

The left-hand side in this expression can be proxied for with the VAR residuals. The volatility of z_t and μ_t changes across regimes $s = 1, ..., S$, and hence we

[8] See e.g. Enders (2003), page 270.

can compute the variance-covariance matrix of the VAR residuals separately for each regime s. This leads to the GMM moment conditions, which are given by

$$A\Omega_{e,s}A' = \Gamma\Omega_{z,s}\Gamma' + \Omega_{\mu,s} \tag{5}$$

where $\Omega_{e,s}$ is the covariance matrix of the residuals (which can compute from the data), and $\Omega_{\mu,s}$ and $\Omega_{z,s}$ are the covariance matrices of the structural and common shocks (which we want to estimate), all in regime s. Note that $\Omega_{\mu,s}$ is diagonal (as we assume the structural shocks to be uncorrelated), and that one common shock implies $\Omega_{z,s} = Var(z_s)$, a scalar. If there are n endogenous variables, $\Omega_{e,s}$ will have $N = n \cdot (n+1)/2$ distinct elements, so that equation (5) delivers N moment conditions for each regime which we summarise in the column vector m_s. Therefore, with S regimes, we obtain $N \cdot S$ moment conditions which can be used for GMM estimation. We choose θ to minimise the objective function

$$\min_{\theta} m'm \tag{6}$$

where

$$m = \begin{pmatrix} m_1 \cdot \frac{T_1}{T} & m_2 \cdot \frac{T_2}{T} & ... & m_S \cdot \frac{T_S}{T} \end{pmatrix}'$$

The vector θ includes the parameters in the matrices A and Γ, as well as the covariance matrices of the shocks, $\Omega_{z,s}$ and $\Omega_{\mu,s}$ for regimes $s = 1...., S$. Note that we multiply the moment conditions of regime s with the relative weight of this regime (T_s is the number of observations in regime s and T is the total number of all observations). Thus we attach more importance to moment conditions that represent a larger number of observations and thus are associated with less uncertainty. This implicitly defines a weighting matrix for GMM estimation.

Our estimation strategy is as follows. First, we estimate the reduced-form model given in equation (4) using OLS. We use the residuals from this regression to pick the regimes: since the volatility of the structural and common shocks changes across regimes, so will the volatility of the VAR residuals. For each regime, we compute the covariance-matrix of the residuals and form the moment conditions according to equation (5). Then, GMM is used to identify the structural form parameters of the original VAR.

3.3 Choosing the regimes

Remember from figure (4) that regimes should be chosen such that the relative volatilities of different structural shocks vary significantly across regimes. Thus, it would be ideal to identify periods where only one variable was volatile, while the others where relatively "tranquil". What precisely is interpreted as "volatile" and "tranquil" could be decided by defining a reasonable volatility threshold. We use two alternative methods to choose regime. The first method uses a simple threshold rule, as in Ehrmann, Fratzscher and Rigobon (2005).

As a robustness check, we also estimate a mixture of distributions model on the residuals to choose regimes. This second approach is discussed in section five.

Here we describe how to use a threshold rule for regime choice, following Ehrmann, Fratzscher and Rigobon (2005). The basic idea is to determine in which periods the EMBIG-residuals, to take an example, are very volatile, while residuals of the other variables are not. To do this we compute standard deviations of residuals for each of the n endogenous variables over fixed windows of 21 days. Let $\sigma_{i,t}$ be the standard deviation of residuals corresponding to endogenous variable i, computed over the period $t-10, ..., t, ..., t+10$. We then define a threshold according to

$$mean(\sigma_{i,t}) + c \cdot st.dev(\sigma_{i,t})$$

where we set $c = 1$.[9] Whenever $\sigma_{i,t}$ is above that threshold, we consider residuals of variable i in period t to be volatile. We then define $n+1$ regimes, where n is the number of endogenous variables. In regime one we include periods where the residuals of all endogenous variables are tranquil. Furthermore, for each endogenous variable i, we identify a regime that includes periods where i's residuals are volatile, but the residuals of other endogenous variables are not.

If more than one variable is above the volatility threshold in some period t, we do not use that period for GMM estimation. Therefore, we may ignore information that is not contained in the data, but that can be obtained by identifying the economic events that volatility periods reflect. Some natural examples are financial crises in emerging markets, which could be interpreted as shocks to EMBIG; tightening cycles in US monetary policy, which would represent shocks to US short term government bond yields; the US auto sector turmoil, which we could capture through shocks to US high yield spreads. Consider the case of the Russian/LTCM financial crisis. According to our definition of volatility, EMBIG spreads are volatile from August 10 until November 11, 1998. US high yield spreads are volatile from August 25, and US long term interest rates from September 1, 1998. Thus, using our mechanical rule, only the period from August 10 to August 24 is included in the regime that identifies EMBIG volatility: the largest part of the data covering the Russian/LTCM crisis is not included at all in the estimation! Clearly, we are loosing some valuable information. However, we know that the whole August-September 1998 period represents a shock to EMBIG spreads originating in the Russian default on August 17. It would therefore seem natural to include the days after August 25 in our EMBIG volatility regime.

Some previous studies have used straightforward economic intuition to identify regimes. Rigobon and Sack (2004) analyse the effect of US monetary policy on asset prices. They use two regimes, one including periods of FOMC meetings and Fed chairman's testimonies to congress, and another including all

[9] Increasing c will decrease the number of periods in the volatility regimes, making identification harder; decreasing c will increase the number of volatility regime periods; however, it is then also more likely that more than one variable above the threshold so that the number of periods not used for GMM estimation rises.

other periods. The idea is that, clearly, monetary policy is more volatile on days when interest rate decisions are taken or when news about interest rate policies emerge. Similarly, Gonçalves and Guimaraes (2006) analyse the relationship between monetary policy and exchange rates in Brazil, identifying periods of Brazilian Central Bank policy meetings as regimes of higher interest rate volatility.

In our case, using economic reasoning for identifying the regimes is not always straightforward, as many events may correspond to shocks to several variables at once. Nevertheless, we also combined the results from using the threshold rule with our economic intuition to define regimes. For example, we allowed for a longer period of the Asian crisis (according to our residual covariances, the Asian crisis lasts only from mid-November to December 1997), attributed all of the Russian crisis period to the EME shock regime, and extended the period of US high yield volatility in spring 2005 to cover the whole period of the US auto sector turmoil. Therefore, there are more observations in the regimes corresponding to EMBIG and US high yield volatility, and less observations in the regime corresponding to tranquility.[10] The resulting covariances from threshold rule and the combination of threshold rule and economic intuition were not very different, and the resulting GMM estimates for the structural coefficients are also very similar. Therefore, we just report the results from the regime choice using the threshold rule.[11]

Figures 5 shows the regimes actually chosen for the case of the EMBIG high volatility regime, as well as the volatility of EMBIG residuals and the threshold that determines when EMBIG residuals are considered to be volatile. Note the spikes in volatility corresponding to the Asian crisis 1997/98, the Russian/LTCM crisis (autumn 1998), and the Brazilian (beginning of 1999) and Argentinean (2001/2002) crises. However, as indicated in the graph, these episodes are only partly included in the EMBIG regime. The reason is that the volatility of other variables - notably US high yields spreads, but also US interest rates - tends to increase as well in times of EME crises. As mentioned above, periods of volatility in several markets are excluded because they would not help with the identification of the structural model.

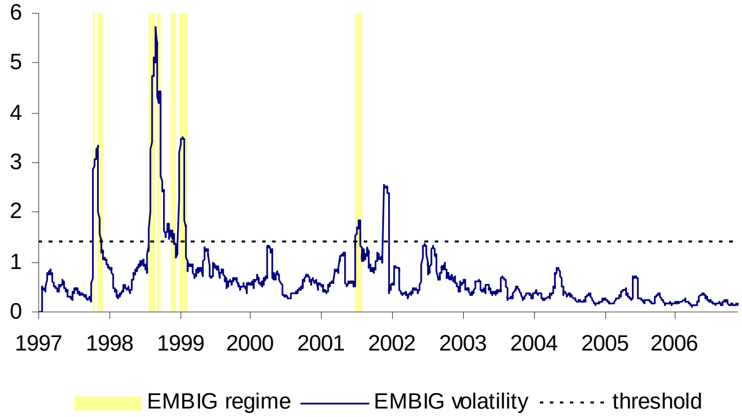
4 Results

This section presents our empirical results. Using "Identification through Heteroskedasticity", we are able to estimate all parameters in the structural model of equation (3). This makes it possible to analyse not only the overall effects of structural shocks on the endogenous variables through the reduced form, but also to assess the importance of various transmission channels. We use data on

[10] With the threshold rule, regime 1 (tranquility) includes 1836 observations, while regime 2 (US 3m volatility) has 166, regime 4 (US 10y volatility) 174, regime 4 (US HY volatility) has 72 and finally regime 5 (EMBIG volatility) 91 observations.

[11] Note also that Rigobon (2003, proposition 3) has shown that estimation by "Identification through Heteroskestacity" remains consistent even if the volatility windows are misspecified.

Figure 5: EMBIG volatility regime periods with threshold rule



bond yields and spreads in first differences to ensure stationarity.

Before discussing our results, let us briefly note some computational issues. Good starting values are very important for the optimization procedure to converge. We use the findings from section two to set starting values for estimation.[12] For the variances of structural shocks, we use the regime variances of the VAR residuals contained in the matrix $\Omega_{e,s}$ as starting values - this should ensure that the starting values are at least roughly of a realistic magnitude. For the variances of the common shock and coefficients in the vector Γ, we use starting values of 1. We also constrain all variances to be positive, and impose constraints on some structural coefficients (for example, we constrain the feedback effects between US short- and long term government bond yields to be positive). This increases the efficiency of the estimation, and also ensures that we pick the right "rotation" of the matrix A (see Ehrmann, Fratzscher and Rigobon, 2005). However, we make sure to check that the constraints imposed are never actually binding. We estimate our model including constant, time trend and five lags in the VAR, and one common shock.[13]

Our estimation yields estimates for the structural-form parameters in A and Γ, as well as for the structural shock variances $\Omega_{\mu,s}$ and $\Omega_{z,s}$. The estimated coefficients in matrix A correspond to the *direct* contemporaneous effects of the various structural shocks on the endogenous variables, as described by the structural form equation (3): the coefficient $A(i,j)$ describes the direct effect of a shock to endogenous variable j on variable i. These coefficients therefore give

[12] We use the built-in MATLAB constrained optimisation routine `fmincon`.

[13] The likelihood ratio test, final prediction error and Akaike information criterion suggest an optimal lag length of 5, while the Schwarz and Hannan-Quinn information criteria point to an optimal lag length of 3. Our intuition is that financial market adjust to new information very quickly, and that including lagged values covering the past work week should be sufficient.

information about the importance of various transmission channels. In order to judge the overall effect of a shock the variable j on variable i, one has to account for all simultaneous feedback effects. This is done in the reduced form model in equation (4) where it can be seen that the coefficients of A^{-1} determine the *overall* effects of structural shocks - i.e., taking into account that effects occur through various direct channels.

The distribution and standard errors for the estimated parameters were obtained using bootstrap: the residuals in each regime are resampled and used to compute new covariance matrices. New parameters are then estimated using GMM. We repeat this procedure 500 times to obtain a set of all coefficients in the model, estimated 500 times. The significance of the estimated parameters can then be judged from the bootstrap p-value. We can also compute the probability distribution function of our estimates (see figures 8 and 8 in appendix B).

Table 3 reports the parameter estimates for both structural-form (matrix A with switched signs) and reduced-form (matrix A^{-1}) coefficients. Bold font indicates that coefficients are statistically significant at the 95% confidence level, according to the bootstrap p-value. See the appendix for detailed bootstrap results on parameter significance.

Table 3: Estimation results using threshold rule for regime choice

(a) **contemporaneous feedback effects: direct**

From... ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m		**0.10**	-0.03	**-0.06**
US 10y	**0.17**		-0.06	**-0.11**
US HY	0.00	**–0.53**		**0.04**
EMBIG	-0.01	0.03	**0.20**	

(b) **contemporaneous feedback effects: overall**

From... ...to	μ_{US3}	μ_{US10}	μ_{USHY}	μ_{EMBIG}
US 3m	**1.02**	**0.13**	**-0.05**	**-0.07**
US 10y	**0.18**	**1.07**	**-0.10**	**-0.12**
US HY	**-0.10**	**-0.57**	**1.06**	**0.10**
EMBIG	-0.02	**-0.09**	**0.21**	**1.02**

Bold coefficients are significant at the 95% confidence level. Panel (a) presents estimated coefficients in matrix A with inverted signs.

Direct effects:

We first discuss direct feedback effects, as presented in panel (a) of Table 3. Begin with the relationship between US government bond yields and EMBIG spreads. Our results imply that a structural shock that increases EMBIG spreads will tend to decrease US government bond yields, where the effect is stronger for long term yields. Both coefficients are highly significant. As mentioned earlier, this finding can be interpreted as reflecting a "flight to quality". The coefficients capturing the reverse effect, however, are close to zero and insignificant, positive for long-term US government bond yields but negative for short term yields. As noted earlier, we would expect a positive sign, as it is conventional wisdom that debt financing costs for risky borrowers tend to increase with risk-free interest rates. However, our finding that the effect is small (and in the case of short rates has the wrong sign) is consistent with the empirical literature on the determinants of sovereign spreads, which seems to be inconclusive as to whether US interest rates can explain the variation of EME credit spreads.[14]

The table also indicates strong comovement of US high yield spreads and EMBIG spreads; note that, perhaps surprisingly, the influence of US high yields spreads on EMBIG is stronger than *vice versa*. The effect of a shock to US long-term interest rates on US high yield spreads is estimated to be strongly negative and highly significant. This result appears very counterintuitive. As mentioned in section two, one possible explanation might be that interest rates tend to increase when the economy is booming; this is likely to coincide with periods when the corporate sector is strong. The reverse effect of US high yield spreads on US interest rates is negative, which could again be interpreted as reflecting a "flight to quality". Finally, notice that the influence of US short-term on long-term yields is stronger than *vice versa*.

Overall effects:

Now, consider the overall effect of structural shocks on the endogenous variables, as given by the coefficients of the matrix A^{-1}. The parameter estimates are summarized in panel (b) of Table 3. Again we concentrate first on the relationship between US long-term government bond yields and EME bond spreads. The overall effects of a shock to EMBIG spreads on US government bond yields are negative, and larger than the direct effects. That suggests that the various transmission channels tend to magnify the "flight to quality" effect. The reverse overall effect of US interest rates on EME bond spreads contradicts the intuitive financing cost/search for yield argument: the coefficients are estimated to be negative, thus have the "wrong" sign, and the coefficient for long-term rates is even significant. The sign of the other coefficients equals the sign of the corresponding direct effects. Note that the coefficients on the diagonal are greater than one: the initial impact of a structural shock on EMBIG spreads is one, but that the effect of that shock is magnified through the feedback effects of other variables so that the overall effect on EMBIG spreads is larger than one.

[14] For example, Kamin and von Kleist (1999) regress emerging market bond spreads on a set of explanatory variables and find that the effect of interest rates in industrialised countries on EME spreads is insignificant, and often has the wrong (negative) sign. See also Eichengreen and Mody (1998).

To summarise our results let us reconsider the two questions posed in the introduction. What is the relationship between US government bond yields and EMBIG spreads? We find that although there may be a weak positive effect of US interest rates on EME bond spreads - in line with our intuition - the overall effect, taking into account feedback effects through other variables, turns out to be negative. How can we explain this sign change from weakly positive to significantly negative? From panel (a) of Table 3, the most likely reason is the indirect feedback through US high yield spreads: a positive shock to US long-term rates will slightly increase EMBIG spreads, but also have a large negative effect on US high yield spreads which in turn influence EME bond markets.

The reverse effect of an EME shock to US interest rates is estimated to be negative and significant: thus, there is strong evidence of flight to quality. However, an EME shock is not necessarily good news for bond markets in mature economies. Structural shocks that raise EMBIG spreads will also raise US high yield spreads, constituting an important channel through which contagion may occur. In the other direction, shocks to the US corporate debt market - for example, the US auto sector shock in 2005 - will also tend to spill over to EMEs. One possible source underlying the comovement of EMBIG and US high yield spreads (in both directions) could be changes in investors' risk aversion and the associated portfolio shifts into less risky assets.

5 Robustness checks

5.1 Parameter stability

As mentioned above, the fundamental assumption underlying our empirical methodology is that parameters are stable. While this assumption is fairly standard, it may sound strange to explicitly consider changing volatility of the structural shocks, while the underlying spillover effects stay the same. One might argue that financial transmission channels are non-linear; for example, the effect of a change in EMBIG spreads on US high yield spreads may be larger in times of EME crises.

Unfortunately, within our methodology it is impossible to check whether parameters are stable across regimes. Given our limited sample, it is not possible to estimate the reduced-form VAR in equation (4) separately for each regime and then test for whether the estimated coefficients stable across regimes (the smallest regime contains only 72 observations). What we can test for, however, is whether parameters are stable across reasonably large subsets of our sample (that is, large enough to estimate at least the reduced-form VAR). We do so formally by using a multivariate version of the Chow test, which tests for stability of the reduced-form parameters, but not for stability of the structural shock variances. If the reduced form parameters, $B = A^{-1}\Pi$ are stable, then so should the structural parameters in matrix A. We therefore re-estimate the reduced-form VAR for two subsamples, from January 1997 up until summer 2000 and from summer 2000 until December 2006. The null hypothesis of parameter stability is not rejected.[15]

To investigate further whether the parameters of the structural model change across time, we split our dataset into two samples and reestimate our model. For the estimation of the model in the two subsamples we use the same regime periods as before, chosen from the analysis of the whole dataset. The estimation in the subsamples is complicated by the fact that regime periods are spread unevenly across the sample: for example, most EMBIG-regime periods are in the first half of the sample (corresponding to the observation that EMBIG volatility has declined substantially in recent years), while US high yield regime periods are mostly in the middle/second half of the sample. We split the sample around summer 2000 to ensure that all regimes in both samples contain enough observations for the model to be identified.

Table 4: Structural-form coefficients in two subsamples

		first sample		
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m		0.12	0.02	-0.07
US 10y	0.19		-0.04	-0.14
US HY	-0.01	-0.54		0.09
EMBIG	-0.02	0.02	0.09	

		second sample		
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m		0.12	0.00	-0.00
US 10y	0.22		-0.07	-0.07
US HY	-0.04	-0.53		-0.00
EMBIG	0.00	0.00	0.40	

Regime choice using threshold rule. Estimated coefficients in matrix A with inverted signs.

The estimated structural coefficients corresponding to direct spillover effects are reported in Table 4. Most coefficients have the same sign in the first and second sample, as well as in our overall estimation results. Moreover, most coefficients are even quantitatively similar. The effects of US short- and long term government bond yields on EMBIG spreads are close to zero for both subsamples. However there are two major changes in the estimation results for the two samples. First, note that the "flight to quality" effect is only half as

[15] Note however that results from the test may be biased because of heteroskedasticity of the structural shocks - see e.g. Toyoda (1974). Therefore, it is likely that the critical value is in fact lower than the one found from the χ^2 - distribution. However, our test results indicate that parameter stability is accepted by a wide margin.

Table 5: Reduced-form coefficients in two subsamples

first sample				
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m	1.02	0.12	0.01	-0.09
US 10y	0.20	1.05	-0.05	-0.17
US HY	-0.12	-0.57	1.04	0.18
EMBIG	-0.02	-0.03	0.09	1.01
second sample				
From...	**US 3m**	**US 10y**	**US HY**	**EMBIG**
...to				
US 3m	1.03	0.13	-0.01	-0.01
US 10y	0.24	1.09	-0.11	-0.08
US HY	-0.17	-0.58	1.06	0.04
EMBIG	-0.07	-0.23	0.42	1.02

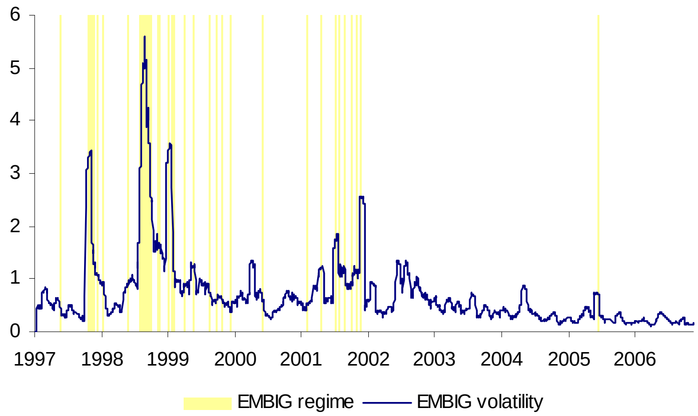
Regime choice using threshold rule.

strong in the latter part of the sample as in the former part. Second, while the spillover effects from EMBIG to US high yield spreads and vice versa are equal in magnitude in the first sample, the effect from US high yield on EMBIG spreads dominates in the second part of the sample.

Next we turn to the reduced-form coefficients, corresponding to the overall contemporaneous effects of structural shocks on the endogenous variables. These are reported in Table 5. There are three main changes between the estimated transmission channels for the first and the second sample. As with the structural coefficients, we observe that the strength of the "flight-to-quality" effect has decreased in the second part of the sample, and that the influence of EMBIG on US high yield spreads is stronger than the reverse effect in the first part of the sample, while the opposite is true in the second sample. A further change occurs in the effect of US government bond yields on EMBIG spreads: the estimated coefficients change from roughly zero in the first part to strongly negative in the second part of the sample.

These changes in coefficients between the two samples may partly reflect difficulties in identification, since due to the rarity of EME crises in recent years there are only very few observations (11) in the EMBIG-volatility regime of the second sample. However, it is also possible that there are more fundamental reasons. Over the years, the composition of the EMBIG index has changed dramatically: while in the 1990s the fraction of investment-grade debt in the EMBIG was about 10%, this number has increased to about 50% in recent years. Therefore, the nature of EME bonds as an asset class may have changed.

Figure 6: EMBIG high volatility regime with endogenous regime choice



5.2 Alternative methods of regime choice

The results presented in the previous sections were derived by using a simple threshold rule to choose volatility regimes. This rule is very easy to implement and works well in practice. However, one may feel uncomfortable with regime choice using an apparently "ad-hoc" rule.

As a robustness check, we present here results using an alternative method which involves estimating a regime switching model to describe the behavior of the residuals/structural shocks. We assume that the stochastic process through which structural shocks are generated is governed by an underlying unobserved variable which we call the state. Thus, if the system is in state $s_t = 1$, structural shocks are assumed to have covariance matrix Ω_1, in state $s_t = 2$ shocks have covariance matrix Ω_2 and so forth. The covariance matrices for each state, as well as the probability that any given observation of the residuals is generated by an underlying state $s_t = j$ can be estimated and thus regimes chosen endogenously. Because of the dimensionality of the problem, we use a multivariate mixture model, rather than a more standard Markov model. Therefore, we only need to estimate the unconditional probabilities of each state and their means and covariances, but no transition matrix. Details are given in appendix A.

The actual regimes chosen differ very much between threshold rule and endogenous regime choice model. Figure 6 plots the regimes periods chosen for the case of EMBIG spreads, together with the volatility of EMBIG residuals (computed over fixed windows of 21 days). Note that the regime periods chosen differ greatly from the previous threshold-method: individual regime periods often only last for two or three days, and are spread out more across the sample. Again, the most important EME crisis events are picked up in the EMBIG high volatility regime.

Table 6: Estimation results using endogenous regimes

(a) **contemporaneous feedback effects: direct**

From... ...to	**US 3m**	**US 10y**	**US HY**	**EMBIG**
US 3m		**0.22**	**-0.11**	-0.04
US 10y	**0.08**		0.03	**-0.14**
US HY	0.02	**-0.55**		**0.06**
EMBIG	**-0.15**	**0.07**	**0.08**	

(b) **contemporaneous feedback effects: overall**

From... ...to	$\boldsymbol{\mu}_{US3}$	$\boldsymbol{\mu}_{US10}$	$\boldsymbol{\mu}_{USHY}$	$\boldsymbol{\mu}_{EMBIG}$
US 3m	**1.03**	**0.28**	**-0.11**	**-0.08**
US 10y	**0.10**	**1.01**	0.01	**-0.14**
US HY	**-0.04**	**-0.55**	**1.00**	**0.14**
EMBIG	**-0.16**	-0.02	**0.10**	**1.01**

Bold coefficients are significant at the 95% confidence level.
In panel (a), estimated coefficients correspond to coefficients in matrix A with inverted signs.

Estimation results are presented in Table 6. Note that most coefficients are equal in sign and also similar in magnitude to our benchmark results, although there are a few differences. Most notably, the direct effect of US long-term government bond yields on EMBIG spreads is estimated not only positive (as in our benchmark specification), but also significant. This suggests again that there may be a positive *direct* effect of US long-term government bond yields on EME spreads (possibly reflecting the "financing cost" argument"), but that the overall effect is negative.

6 Concluding remarks and work going forward

This paper has analysed how shocks are transmitted across bond markets in emerging market economies and mature markets. We used a recently developed method, "Identification through Heteroskedasticity", to identify all parameters in a structural VAR, without imposing ad-hoc assumptions. This allowed us to quantify not only the overall spillover effects, but also the importance of alternative transmission channels.

We found strong evidence for the "flight to quality" phenomenon, while the "financing cost channel" was estimated to be insignificant, and even with the wrong sign in overall effects. Concerning the comovement of US high yield spreads and EMBIG spreads we found that spill over effects in both ways are equally important. Therefore, the feedback between EME bond markets and markets for risky debt in developed countries appears to be an important channel through which crises in EMEs can negatively affect mature markets. We carried out robustness checks to show that our results are not sensitive to the exact choice of the regime windows, and also showed that our assumption of stable parameters was justified.

Apart from providing some interesting new evidence on financial transmission channels between emerging and mature bond markets, our analysis can hopefully be of further use for monitoring the development of international financial markets. Comparing how estimated coefficients change as the sample grows might lead to interesting insights into how the importance of different transmission channels has changed. This can help to evaluate the risk that shocks in EMEs could spill over to mature markets.

References

[1] Allen, Franklin and David Gale (2000), "Financial Contagion," *Journal of Political Economy* 108, pp. 1-33.

[2] Calvo, Guillermo and Enrique Mendoza (2000), "Rational contagion and the globalization of securities markets," *Journal of International Economics* Vol. 51, No. 1, pp. 79-113.

[3] Carporale, Guglielmo Maria, Andrea Cipollini and Panicos O. Demetriades (2005), "Monetary policy and the exchange rate during the Asian crisis: identification through heteroskedasticity," *Journal of International Money and Finance* 24, pp. 39-53.

[4] Cappé, Oliver (2001), "A set of MATLAB/OCTAVE functions for the EM estimation of mixtures and hidden Markov models," available at http://www.tsi.enst.fr/~cappe/h2m/.

[5] Chari, Varadarajan and Patrick J. Kehoe (2003), "Hot Money," *Journal of Political Economy*, 111, pp. 1262-1292.

[6] Dornbusch, Rudiger, Y.C. Park and S. Claessens (2000), "Contagion: understanding how it spreads," *The World Bank Research Observer* 15, pp. 177-197.

[7] Dungey, Mardi, Renée Fy, Brenda González-Hermosillo and Vance L. Martin (2003), "Empirical modelling of contagion: a review of methodologies," mimeo.

[8] Favero, Carlo A. and Francesco Giavazzi (2002), "Is the international propagation of financial shocks non-linear? Evidence from the ERM," *Journal of International Economics* 57, pp. 231-246.

[9] Gagnon, Louis and G. Andrew Karolyi (2006), "Price and volatility transmission across borders," mimeo.

[10] Goldstein, Itay and Ady Pauzner (2004), "Contagion of Self-Fulfilling Financial Crises due to diversification of investment portfolios," *Journal of Economic Theory*, 119, pp. 151-183.

[11] Ehrmann, Michael, Marcel Fratzscher and Roberto Rigobon (2005), "Stocks, bonds, money markets and exchange rates: measuring international financial transmission," *NBER Working Paper* No. 11166.

[12] Eichengreen, Barry, and Ashoka Mody (1998), "What explains changing spreads on emerging-market debt: fundamentals or market sentiment?" *NBER Working Paper* No. 6408.

[13] Enders, Walter (2003), *Applied Econometric Time Series*, Wiley.

[14] Forbes, Kristin and Roberto Rigobon (2002), "No contagion, only interdependence," *Journal of Finance* 57, No. 5, pp. 2223-2261.

[15] Gonçalves, Carlos Eduardo S. and Bernardo Guimaraes (2006), "Monetary policy and the exchange rate in Brazil," mimeo, London School of Economics.

[16] Hamilton, James D. (1994), *Time series analysis*, Princeton University Press.

[17] Kamin, Steven B., and Karsten von Kleist (1999), "The evolution and determinants of emerging market credit spreads in the 1990s," *BIS Working Paper* No. 18.

[18] King, Mervyn A. and Susil Wadhwani (1990), "Transmission of volatility between stock markets," *Review of Financial Studies* 3, pp. 5-33.

[19] King, Mervyn A., Enrique Santana and Sushil Wadhwani (1994), "Volatility and links between national stock markets," *Econometrica* 62, pp. 901-933.

[20] Kodres, Laura E., and Matt Pritsker (2002), "A rational expectations model of financial contagion," *Journal of Finance* 57, pp. 769-799.

[21] Kyle, Albert and Wei Xiong (2001), "Contagion as a wealth effect," *Journal of Finance* 56, pp. 1401-1440.

[22] Pesaran, Hashem M. and Andreas Pick (2006), "Econometric issues in the analysis of contagion," *Journal of Economic Dynamics and Control*, forthcoming.

[23] Rigobon, Roberto (2003), "Identification through heteroskedasticity," *Review of Economics and Statistics* 85, pp. 777-792.

[24] Rigobon, Roberto and Brian Sack (2003), "Measuring the response of monetary policy to the stock market," *Quarterly Journal of Economics* 118, pp. 639-669.

[25] Rigobon, Roberto and Brian Sack (2004), "The impact of monetary policy on asset prices," *Journal of Monetary Economics* 51, pp. 1553-1575.

[26] Sáez, Lucía Cuadro, Marcel Fratzscher and Christian Thiemann (2007), "The transmission of emerging market shocks to global equity markets," *ECB working paper* No. 724.

[27] Toyoda, Toshihisa (1974), "Use of the Chow test under heteroskedasticity," *Econometrica* 42, pp. 601-608.

[28] Veldkamp, Laura (2006), "Information Markets and the Comovement of Asset Prices," *Review of Economic Studies*, 73, pp. 823-845.

7 Appendix A: estimating regimes using a multivariate mixture model

This appendix provides more detailed information on how volatility regimes can be estimated using a multivariate mixture model.[16] Let be $\mathbf{e}_t$ a vector containing the period t VAR residuals,

$$\mathbf{e}_t = \left[\begin{array}{cccc} e_{us3m,t} & e_{us10y,t} & e_{ushy,t} & e_{embig,t} \end{array} \right]'$$

and assume that for each period t, $\mathbf{e}_t$ is drawn from a different probability distribution, depending on the current realization of an underlying, unobserved variable s_t which we call the state (some of these states will later correspond to our volatility regimes). Assume that there are N states, so that $s_t = \{1, 2, ..., N\}$. Let the unconditional probability that a given state, say $s_t = j$, is realized in t be given by

$$p\left(s_t = j; \boldsymbol{\theta}\right) = \pi_j,$$

where $\boldsymbol{\theta}$ is a vector that contains all parameters of the model, as defined below. If the underlying state in t is $s_t = 1$, our residuals $\mathbf{e}_t$ are assumed to have been drawn from a multivariate normal distribution with mean $\boldsymbol{\mu}_1$ and covariance matrix $\boldsymbol{\Sigma}_1$; if the current state is $s_t = 2$, the residuals are drawn from a normal distribution with mean $\boldsymbol{\mu}_2$ and covariance matrix $\boldsymbol{\Sigma}_2$. In general, we have

$$\mathbf{e}_t | s_t = j; \boldsymbol{\theta} \sim N\left(\boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j\right)$$

The corresponding probability density function (conditional on $s_t = j$) is denoted by $f\left(\mathbf{e}_t | s_t = j; \boldsymbol{\theta}\right)$. The vector $\boldsymbol{\theta}$ summarizes all parameters in our model. Thus $\boldsymbol{\theta}$ will contain the unconditional probabilities of the N states, $\pi_1, ..., \pi_N$, the elements of the mean vectors $\boldsymbol{\mu}_j$ for each state $j = 1, ..., N$, and the unique elements of the N covariance matrices $\boldsymbol{\Sigma}_j$.

The idea is then to choose the parameters in $\boldsymbol{\theta}$ such that the probability of observing our sample of residuals is maximized. To compute the likelihood function, consider first the joint probability of observing $\mathbf{e}_t$ while the underlying state is $s_t = j$. This is given by

$$p\left(\mathbf{e}_t, s_t = j; \boldsymbol{\theta}\right) = f\left(\mathbf{e}_t | s_t = j; \boldsymbol{\theta}\right) \cdot \pi_j$$

Summing over all possible states N, the unconditional density of $\mathbf{e}_t$ is then

$$f\left(\mathbf{e}_t; \boldsymbol{\theta}\right) = \sum_{j=1}^{N} p\left(\mathbf{e}_t, s_t = j; \boldsymbol{\theta}\right)$$

From this, the log likelihood is computed as

$$L\left(\boldsymbol{\theta}\right) = \sum_{t=1}^{T} \log f\left(\mathbf{e}_t; \boldsymbol{\theta}\right)$$

[16] For an introduction into the formulation and estimation of univariate mixture distributions see Hamilton (1994), chapter 22.

The likelihood function is then maximized with respect to $\boldsymbol{\theta}$ using the EM algorithm. This algorithm has the advantage that it increases the value of the likelihood function in each iteration; thus, if the algorithm converges, we have found the maximum of the likelihood functions. The estimation was performed using the MATLAB toolbox *h2m*, written by Oliver Cappé.

Once the parameters have been estimated, we can compute the probability that the underlying state in some period t is $s_t = j$. This is done using Bayes' rule:

$$p\left(s_t = j|\mathbf{e}_t, \boldsymbol{\theta}\right) = \frac{p\left(\mathbf{e}_t, s_t = j; \boldsymbol{\theta}\right)}{f\left(\mathbf{e}_t; \boldsymbol{\theta}\right)}$$

We then say that the underlying state in period t is j if this is the state which has the highest conditional probability: formally, $s_t = j$ if $p\left(s_t = j|\mathbf{e}_t, \boldsymbol{\theta}\right) > p\left(s_t = i|\mathbf{e}_t, \boldsymbol{\theta}\right)$ for all i.

Next, we need to decide which of the N states correspond to our volatility regimes. Recall that for identification purposes, we would like to choose $1 + n$ regimes: one "tranquility" regime, and n regimes where only one variable is volatile, while the others have a low volatility. Thus pick those of the N states that best match this description. In practice, this can be done using a simple formula. Let σ_{ij}^2 denote the standard deviation of the residual of endogenous variable j in state i - the (j,j)th entry in $\boldsymbol{\Sigma}_i$. Then we choose that state i as volatility regime for variable j that maximizes

$$\max_i \left(\left(\sigma_{ij}^2\right)^\tau - \sum_{k \neq i} \sigma_{kj}^2 \right) - \sum_{h \neq j} \left(\sigma_{ih}^2 - \sum_{k \neq i} \sigma_{kh}^2 \right)$$

where $\tau \geq 1$ is a parameter that determines how much weight is placed on the variance of the variable that is volatile in regime i, as compared to the other, non-volatile variables. For the tranquility regime, we use the formula

$$\min_i \sum_{j=1}^{N} \left(\left(\sigma_{ij}^2\right)^\tau - \sum_{k \neq i} \sigma_{kj}^2 \right)$$

How should the number of states, N, be determined? We take $N = n^2$ states are need to cover all possible volatility combinations that can arise if each variable is either volatile or not.[17] For example, there could be one state where only US short rates are volatile, another state where US short and long rates are volatile, a third state where US short rates and US high yield spreads are volatile and so forth. We set starting values for the EM algorithm to point estimation in the direction of such volatility combinations.

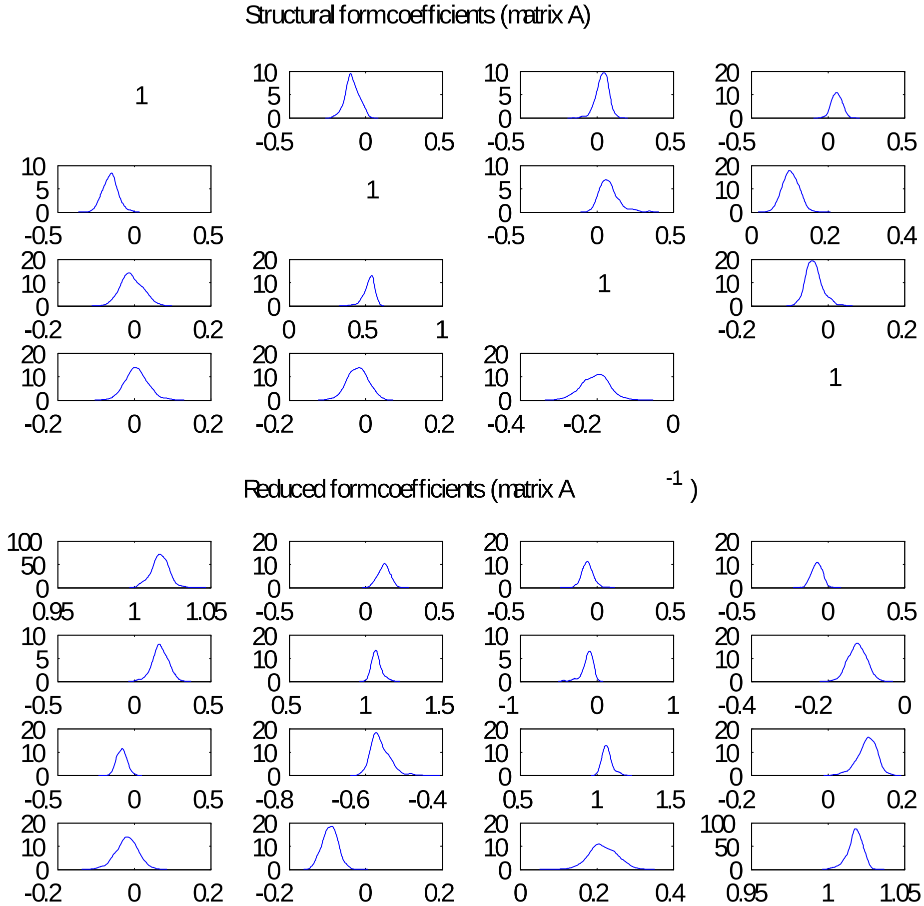
It is worth noting that the dimension of the problem can become quite large, so that the algorithm may take long to converge. With four variables and 16

[17] Of course, the estimated variances do not need to confirm intuition; for example, one variable could be estimated to have a low variance in all states, while another variable exhibits several different levels of volatility across states. However, allowing for a greater number of states would further increase the dimensionality of the maxization problem.

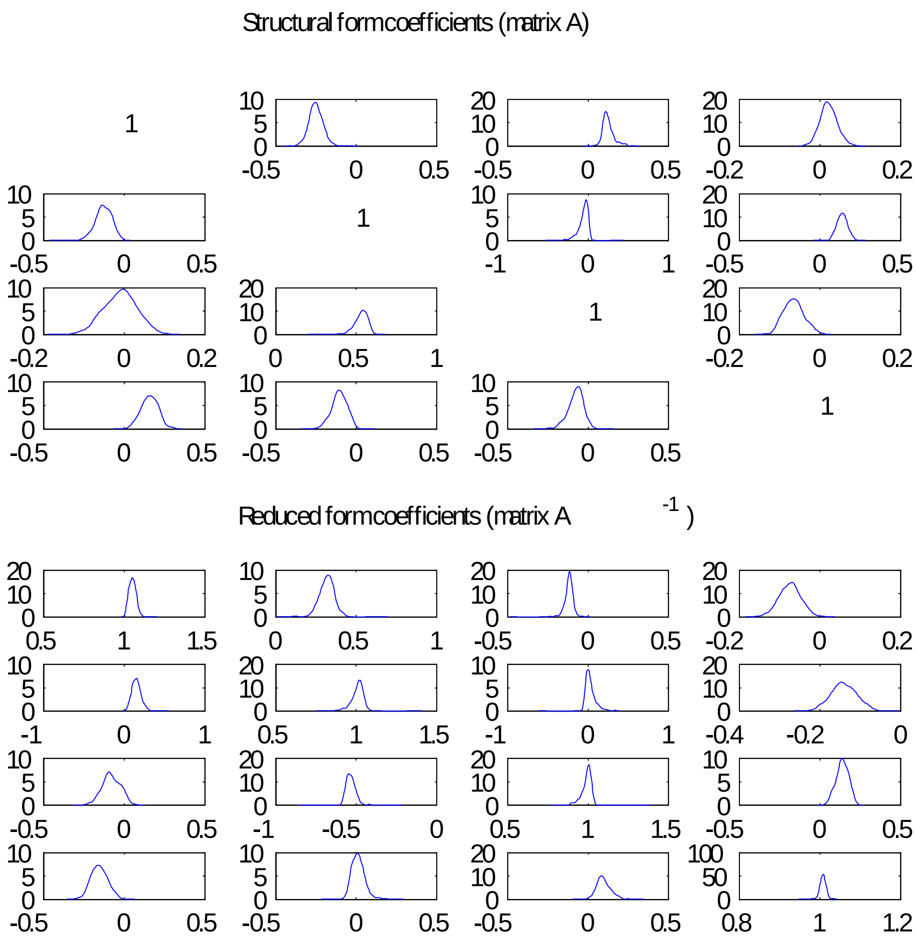
states, we need to estimate 16 unconditional probabilities π_j, plus 16 times 4 means μ_{ij}, plus 16 times 10 covariances - in total 240 parameters (which in our case must be estimated from around 2500 observations). Convergence is significantly faster if the covariance matrices $\mathbf{\Sigma}_j$ are diagonal. Unfortunately, the VAR-residuals will be correlated (unlike the underlying structural shocks which we are trying to uncover).[18] Alternatively, we could also work with the standard deviations of the residuals - however, in this case it is not clear whether or not it is reasonable that, for example, $\sigma^2_{us10,t}$ and $\sigma^2_{embig,t}$ will be independent in a given state.

[18] Recall that $e_t = A^{-1}(\Gamma z_t + \mu_t) + \varepsilon_t$, where ε_t represents the error in estimating our reduced-form parameters $A^{-1}\Pi(L)$.

8 Appendix B: tables and graphs



Distribution of estimated coefficients (threshold ruld) from 500 bootstrap replications



Distribution of estimated coefficients (endogenous regime choice) from 500 bootstrap replications

Table 7: Bootstrap results for benchmark specification (threshold rule)

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	-0.1709***	-0.1571	0.0501	0
US 3m→US HY	-0.0018	-0.0090	0.0264	0.3660
US 3m→EMBIG	0.0064	0.0091	0.0293	0.3920
US 10y→US 3m	-01001**	-0.0905	0.0506	0.0440
US 10y→US HY	0.5316***	0.5217	0.0383	0
US 10y→EMBIG	-0.0209	-0.0221	0.0254	0.1840
US HY→US 3m	0.0270	0.0358	0.0408	0.1580
US HY→US 10y	0.0606*	0.0804	0.0678	0.0640
US HY→EMBIG	-0.2030***	-0.2048	0.0319	0
EMBIG→US 3m	0.0552**	0.0571	0.0361	0.0380
EMBIG→US 10y	0.1048***	0.1048	0.0216	0
EMBIG→US HY	-0.0379**	-0.0359	0.0191	0.0480

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0221***	1.0170	0.0061	0
μ_{us3m} →US 10y	0.1828***	0.1684	0.0511	0
μ_{us3m} →US HY	-0.0962***	-0.0798	0.0337	0.0040
μ_{us3m} →EMBIG	-0.0223	-0.0221	0.0294	0.2260
μ_{us10y} →US 3m	0.1273***	0.1227	0.0443	0
μ_{us10y} →US 10y	1.0662***	1.0708	0.0326	0
μ_{us10y} →US HY	-0.5701***	-0.5601	0.0285	0
μ_{us10y} →EMBIG	-0.0943***	-0.0921	0.0200	0
μ_{ushy} →US 3m	-0.0498**	-0.0615	0.0372	0.0420
μ_{ushy} →US 10y	-0.0950***	-0.1207	0.0769	0.0100
μ_{ushy} →US HY	1.0585***	1.0668	0.0340	0
μ_{ushy} →EMBIG	0.2132***	0.2162	0.0334	0
μ_{embig} →US 3m	-0.0717**	-0.0733	0.0363	0.0200
μ_{embig} →US 10y	-0.1254***	-0.1262	0.0227	0
μ_{embig} →US HY	0.1052***	0.1019	0.0230	0
μ_{embig} →EMBIG	1.0192***	1.0178	0.0045	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using threshold rule.

Table 8: Bootstrap results for regime choice with multivariate mixture model

Estimated structural-form coefficients (matrix A)

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
US 3m→US 10y	-0.0764***	-0.1278	0.0509	0
US 3m→US HY	-0.0206	-0.0098	0.0408	0.4160
US 3m→EMBIG	0.1542***	0.1578	0.0518	0
US 10y→US 3m	-0.2206***	-0.2491	0.0452	0
US 10y→US HY	0.5476***	0.5303	0.0432	0
US 10y→EMBIG	-0.0673***	-0.1046	0.0480	0.0020
US HY→US 3m	0.1105***	0.1254	0.0368	0
US HY→US 10y	-0.0280	-0.0596	0.0713	0.1380
US HY→EMBIG	-0.0785**	-0.0758	0.0482	0.0420
EMBIG→US 3m	0.0338	0.0218	0.0212	0.1480
EMBIG→US 10y	0.1348***	0.1383	0.0330	0
EMBIG→US HY	-0.0633***	-0.0649	0.0249	0.0060

Estimated reduced-form coefficients (matrix A^{-1})

		bootstrap		
	Point estimate	**mean**	**standard error**	**p-value**
μ_{us3m} →US 3m	1.0317***	1.0517	0.0218	0
μ_{us3m} →US 10y	0.0986***	0.1518	0.0551	0
μ_{us3m} →US HY	-0.0426*	-0.0798	0.0565	0.0800
μ_{us3m} →EMBIG	-0.1558***	-0.1548	0.0509	0
μ_{us10y} →US 3m	0.2838***	0.3175	0.0495	0
μ_{us10y} →US 10y	1.0089***	1.0083	0.0416	0
μ_{us10y} →US HY	-0.5478***	-0.5310	0.0390	0
μ_{us10y} →EMBIG	-0.0188	0.0138	0.0438	0.3940
μ_{ushy} →US 3m	-0.1124***	-0.1191	0.0306	0
μ_{ushy} →US 10y	0.0064	0.0277	0.0650	0.3600
μ_{ushy} →US HY	1.0003***	0.9902	0.0372	0
μ_{ushy} →EMBIG	0.0963***	0.0974	0.0445	0.0040
μ_{embig} →US 3m	-0.0803***	-0.0743	0.0270	0.0040
μ_{embig} →US 10y	-0.1390***	-0.1404	0.0312	0
μ_{embig} →US HY	0.1386***	0.1392	0.0382	0
μ_{embig} →EMBIG	1.0139***	1.0073	0.0086	0

*,** and *** denote significance at the 90%, 95% and 99% level, respectively. Results from 500 bootstrap replications. Regime choice using multivariate mixture model.